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Confident and ‘wrong’?
Towards a mindful use of visuals in project portfolio decisions

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Abstract
Portfolios exhibit a degree of complexity that easily exceeds the human ability to achieve optimal decisions through mere intuition. Making sense of this complexity involves a wise use of larger quantity of data. Visuals can help the analysis of more data through different perspectives. Yet, visuals can also aggravate the challenges involved in portfolio decisions. Inspired by Weick and Sufcliffe’s concept of mindfulness, we conducted an experiment with 204 participants to explore how to use visual mindfully in project portfolio context. The results suggest that use of purposeful and familiar visuals contributes to a more mindful engagement with visuals.

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Keywords
Project portfolio management, decisions, sense making, mindfulness

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1. Introduction

We are under pressure to digest increasing amount of data (Keim et al, 2010; LaValle, 2011; McAfee & Brynjolfsson, 2012) in shorter periods of time. Project portfolio decisions are no exception. The available information used to support project portfolio decisions is often vast, ever changing, ambiguous and characterized by uncertainties and interdependencies between various decision parameters (Archer & Ghasemzadeh, 1999). Portfolios exhibit a degree of complexity that easily exceeds the human ability to achieve optimal decisions through mere intuition. Making sense of this complexity involves a wise use (Martinsuo and Lehtonen, 2007) of larger quantity of data (Bourgeois III & Eisenhardt, 1988) in project portfolio decisions.

Yet, the extant research suggests that our cognition poses limits to our ability to make sense of the data we are confronted with. The assumption of rationally behaving decision makers only holds to a certain degree. Due to a wide range of observed cognitive biases, the behavior of decision makers can be best described as bounded rationality (Simon, 1955). Our limited short-term memory makes us feel quickly overwhelmed (Ware, 2012). We hence seek satisficing solutions, and not optimal ones (Simon, 1955). Moreover, "we actively seek out evidence that confirms our expectations and avoid evidence that disconfirms them" (Weick and Sutcliffe 2007, p. 25ff). Therefore, the use of larger amounts of data is usually associated with an increase in confidence, but not necessarily to an improved understanding of the situation (Omodei et al., 2005; Tsai et al, 2008). As we search for data that confirms our expectations, engagement with more data does not necessarily lead to an engagement with alternative perspectives on the same problem. The consequence is that more data does not guarantee better decisions and can lead to overconfidence.

We content that today's uncertain, complex and rapidly changing project portfolio context demands an improved engagement with data. Visuals can leverage natural perception skills (Ware, 2012), improve our ability to process information, and thereby help overcome cognitive limitations and provide accelerated and improved insight into decision problems (Card et al, 1999). Yet, visuals can aggravate the challenges involved in portfolio decisions; they can also deceive, intensify confirmatory biases, extend our blind spots, and hence hamper instead of help cognition (Hill, 2004). Inspired by Weick and Sufcliffe (2007) concept of mindfulness, we ask how could we encourage people involved in project portfolio decisions to use visual mindfully.

Drawing on the literature on sensemaking, data visualization, visual analytics and data cognition, this article presents findings from an experimental research study with over 200 participants, which investigated whether visuals can enhance our ability to engage with data mindfully, i.e. to analyze more data leading to improved decisions, while not becoming overwhelmed nor overconfident.

2. Theoretical Rational and propositions: Sensemaking

The sensemaking process is central to our engagement with data. Drawing on Weick (1995), Weick et al (2005) and Klein et al (2006), the next paragraphs explain sensemaking in simple terms. While this may be tedious to many academics familiar with the sensemaking literature, it is useful to introduce key assumptions building up to our hypothesis later in this section.

Sensemaking can be understood as a process of creating a frame of reference (also known as mental model). Such frame gives meaning to a problem, and thereby guides decisions and actions. Everyone uses frames of reference that help explain the world around us. We are also constantly refining our frames, as we interact with our context and sense ‘cues’. Cues include a wide range of things, such as charts and data in project reports, a conversation with stakeholders, or even a strange gesture or look.

As people encounter cues that are inconsistent with their current frames, they can either discard the cues and keep an existing frame or question the frame. The sensemaking process is triggered as current frames are questioned. Therefore, sensemaking is an active process, where people consciously search for explanations for problems. Developing a frame is also a recursive process of fitting cues into frames and the frames into the cues.

Sensemaking can be reduced to the following process: First, an initial frame is elaborated as one searches and filters data from the context. We then start the process of re-framing, where the first frame (also termed anchoring frame) is questioned, and new, more elaborate, frames are constructed (Klein et al, 2006b). In the process of reframing, we put the emerging frame into question. We search for inconsistencies and anomalies, judge plausibility and gauge data quality. In the portfolio decision context, decision makers could, for example, ask the following questions: Are all strategic objectives being address? Do we have a balance of trade-offs, such as risk and reward? Are we innovative enough? Do projects address key stakeholders’ interests? By asking such questions, different potential frames are compared, combined and discarded in search of acceptable, coherent new frames. Hence, sensemaking is considered an ongoing process, as ‘data’ is constantly changing as are our frames. Sensemaking is also retrospective, as people search for an understanding of the problem by looking back into what had happen and why.

As Klein et al explain, “People react to data elements” (or cue) “by trying to find or construct a story, script, a map, or some other type of structure to account for the data. At the same time, their repertoire of frames—explanatory structures—affects which data elements they consider and how they will interpret these data.” (Klein, Phillips, Raill, & Peluso, 2007) That is why sensemaking is considered a two-way process of fitting cues into frame and frame into cues.
In this process, “(t)he specific frame a person uses depends on the data or information that are available and also on the person’s goals, the repertoire of the person’s frames, and the person’s stance (e.g., current workload, fatigue level, and commitment to an activity).” (Klein, Phillips, Raill, & Peluso, 2007). Hence, frames are also influenced by personal preferences, experience, expert knowledge, political stance, and hence idiosyncratic. They also embed a system of rules, principles, etc., used in organizing and guiding individual behavior (Goffman, 1974).

As the new frame leads to actions, they also shape the context and change the situation. That is why the sensemaking process not only responds to, but also constructs the context around us (Weick et al., 2005). Likewise, it will also inform the development of our identities and roles (Weick, 1995).

Finally, although people seek to develop a coherent frame to understand a specific situation in complex contexts it is possible to entertain several, even contradicting frames at a point in time.

In summary, within this research sensemaking is defined as a conscious, active, social, idiosyncratic, retrospective and ongoing process of creating an understanding of a disrupting situation or problem. It is based on a two-way process fitting the cues into a frame (a mental model, or an initial understanding) and the frame into the cues. In the portfolio context, organizational actors will develop multiple frames, negotiate which of them will become the most accepted, and converge into an understanding that will guide decisions, actions and construct identities.

Visuals in sensemaking process

This particular research focuses on the role of data displayed visually in the sensemaking process. Visuals function as anchoring frames as well as cues in the sensemaking process.

Visuals can encourage the construction of a more elaborated frame at least three reasons: a) visuals are effective vehicles to understand large and complex quantity of data (Ware, 2012); b) visuals occupy similar amount of space in our limited short-term memory, yet embed more data (Few, 2010); and c) visuals function as 'holding ground', and so extend our short-term memory (Henderson, 1999), which in turn helps us consider more data through more perspectives. Therefore, the use of multiple visuals enables cognition of even greater quantities of data, and potentially distinct perspectives of the portfolio problem.

The challenge: cutting corners

Yet, engagement with several visuals will not necessarily produce better results. Research suggests that the function describing the relationship between the amount of data analyzed and analytical performance is rather curvilinear than linear: having more data available is only helpful to a certain extent, thereafter, more data does not lead to a more accurate or better understanding of the situation (Rudolph, 2003). It is reasonable to expect that, as with data, the engagement with a larger amount of visuals could lead to information overload and to a curvilinear relationship between number of visuals and cognition.

An even more relevant problem is that the engagement with a large enough number of visuals is not intuitive; actually, it is quite the opposite. Our search for an adequate understanding of a problem (or frame) is driven by plausibility, not accuracy; as we find a frame that appears to fit, we are likely not to continue searching for cues (Weick, 1995). We search for satisficing, not optimal solutions (Simon, 1955).

Visuals intensify this impulse, "because our minds prefer to take the fastest and easiest route to making a decision, and because image or imagistic text offer shortcuts towards the endpoint of making a decision, then images … will prompt the viewer to make a relatively quick decision, largely ignoring the more analytical, abstract information available in verbal form" (Hill, 2004, pp. 33) This is confirmed by Lurie and Mason (2007)'s empirical study in marketing decisions, which suggests that visuals restrict instead of increase the amount of information used.

The immediacy of visuals can also make us more vulnerable to cognitive biases, in particular confirmation bias, to favor information that confirms our beliefs and to discredit information that points to the opposite (Carroll, 2012); if a visual strongly supports someone's interests, the person may not engage with other visual and search for alternative frames. This would suggest that people will tend not to engage with different visuals, and keep with the ones which provide the quickest, easiest and most convenient understanding of the problem. Therefore:

Proposition 1: There is a non-linear relationship between number of visuals used and cognition of data.

Overconfidence is another potential result of the engagement with a large quantity of information, so people become overconfident but not increasing correct (Omodei et al., 2005). For example, Tsai et al (2008) found that when provided with more relevant information, judges became more confident than accurate. Such decision bias is particularly pronounced in more subjective and complex tasks (Klayman et al, 1999) such as a portfolio decision. If this notion also applies to visuals, then it can be expected that the engagement with larger numbers of visuals would increase confidence to a greater degree than cognition, and hence it could also contribute to overconfidence. Therefore, we suggest:

Proposition 2: The use of more visuals contributes to an increase in confidence and can lead to overconfidence.

Towards a mindful engagement with data

Mindfulness is understood as "a rich awareness of discriminatory detail. By that we mean that when people act, they are aware of context, of ways in which details differ (in other words, they discriminate among details), and of deviations from their expectations." (Weick and Sufcliffe 2007, pp. 34) The overarching idea is to keep high level of alertness and awareness of context, so organizational actors can capture and make sense of early signals of deviations or of unexpected events.

Weick and Sufcliffe suggest five principles of mindfulness: reluctance to simplify, preoccupation with failure, sensitivity to operations (principles of anticipation) and commitment to resilience, and deference to expertise (principles of containment).

In the context of this research, mindfulness refers to the ability of decision maker not to short cut the sensemaking process, and instead engage with different data to create a more comprehensive understanding of the problem, and make informed decisions. In other words, we explore whether a mindful engagement with more visuals can help people 'fight against' the desire to shortcut the sensemaking process. In this respect, and in the context of the five principles proposed by Weick and Sufcliffe, our study focuses on principles of anticipation, and in particular the reluctance to simplify.

Weick and Sufcliffe (2007) developed the concept of mindfulness in the context of repetitive and sensitive operations in mind, as can be found in healthcare, nuclear or aviation industries. The ideas of mindfulness have been previously applied to risk management in project contexts (Deyner et al 2011). Yet, Weick and Sufcliffe's concepts have not been applied to the project portfolio decisions, and in particular to the use of data in this context. This article will explore this gap.

Mindfulness through use of familiar visuals

Sensemaking is influenced by people's own interests, experience, professional knowledge, etc. Analogously, we argue that sensemaking is also influenced by visual experiences and the familiarity of decision maker with a specific visual.

Language is the vehicle of cognition, and hence cognition and language are intrinsically related. This means that our cognition can be only as complex as our language skills allow (J. W. Geraldi, 1991). Visuals are a type of language (Bell et al., 2014); which is different from (Bertin, 1967 (2010)) and a complement to verbal language in our cognition process. Thus, since language has an impact on cognition and visuals are a form of language, visual literacy, i.e. the ability to use visual language and specifically visual experiences and familiarity with specific visuals have an impact on cognition.

The following two examples elucidate this effect. First, the understanding how a visual works will help us use a visual more effectively. An individual, who is familiar with the use of logic flow diagrams, will be able to interpret it easily. However, anyone who is not familiar with this type of visual, will first need to gain an understanding of the visual and how use it. Second, the knowledge of different types of visuals can help us ask different questions. For example, familiarity with the logic flow visual can help develop more complex arguments in a more precise and logical manner, and thereby possibly avoid cognitive errors (Fischhoff, 2006). Third, familiar elements, such as colors, icons, layouts, styles etc. can be leveraged to achieve cognitive effects (Bertin, 1967), as less effort is required to understand the visual and instead more attention can be given to to its content.

Familiarity with visuals will make the use of a visual more effective and hence improve cognition, especially when a decision maker has to perform data analysis and judgment under time pressure and therefore cannot afford the time to explore unknown visuals[1]. Moreover, if a person is familiar with different kinds of visuals, he or she can engage with larger amount of perspectives with greater ease. We therefore suggest:

Proposition 3: Cognition of data is positively influenced by familiarity with the visuals used.

Furthermore, familiarity is likely to lead to higher levels of confidence in interpreting a visual accurately. For example, most project managers are familiar with project S-curves and will immediately recognize project slippage at a point in time (t'), as the actual progress (solid line) trails the target progress (dotted line), depicted in the illustration below. Familiarity with this visual representation will lead to greater confidence in its interpretation compared to someone who is confronted with an S-curve for the first time.

[1] The assessment of this proposition is not straightforward, as this effect needs to be controlled by someone's ability to understand unfamiliar visuals (a type of visual literacy). Yet, it is reasonable to expect that familiarity of visuals will override the ability to understand unfamiliar visuals, as the latter will take more time than the former.

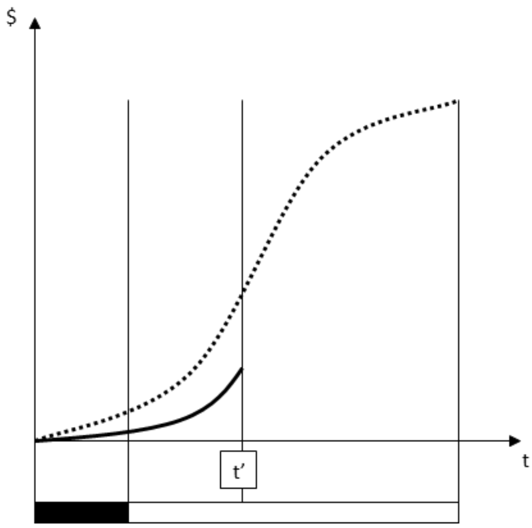

Figure 1: Project S-curve

Yet, anyone familiar with the same type of visual, even with different data, may recognize different patterns, connect the new visual with past experiences and interpretations of a previous project or portfolio decision problem. Such experience is fundamental for a competent evaluation of data. Therefore, we suggest:

Proposition 4: The use of familiar visuals contributes to an increase in confidence and can lead to overconfidence.

Mindfulness through interactive visuals

In recent years, there has been a shift in our understanding of visualization. Visuals are no longer just *"static objects, printed on paper or fixed media, modern visualization is a very dynamic process, with the user controlling virtually all stages of the procedure, from data selection and mapping control to color manipulation and view refinement."* (Ward et al., 2010, p. 26). Interactivity opens exciting opportunities, moving the focus from producing and disseminating information to interacting with it. Interactive visuals enable the user to organize and reorganize data in order to think and to probe ideas, and access the results of queries more reliably and confidently (Keim et al, 2010). In this process, visuals allow users to enhance their frames, as they "melt" into the sensemaking process.

Interactive visuals also offer the potential to simplify the decision process, by hiding much of its complexity. For example, an interactive visual can embed interdependencies between projects, or an allocation of resources, in a way that transforms the decision process into a simulation, where optimal portfolios of projects can be selected by "trial and error", without requiring a deep understanding of the data, interrelationships and the portfolio management objectives per se. In this respect, decisions could even improve in terms of achieving pre-determined objectives, as the portfolio management logic is embedded in such visuals, yet they do not necessarily draw on deeper understanding of the problem. A mindful use of interactive visuals would rather hinge on the reduction of complexity to focus the attention on a more strategic understanding of the problem.
Hence, we suggest:

Proposition 5: Cognition of data is positively influenced by use of interactive visuals.

Mindfulness through purposeful visuals

A larger number of visuals could also encourage a wiser use of data. Visuals can help us to see different perspectives of the portfolio problem. Like a complex geometric form, the portfolio problem has different facets and can be examined through different perspectives. Each visual could provide one or several perspectives of the portfolio problem, e.g. an insight into the portfolio balance, the strategic alignment of the projects with the portfolio or their individual and cumulative benefits contribution etc. As decision makers analyze different visuals, they engage with different perspectives, which enable them to elaborate, question and build more comprehensive frames to understand the portfolio problem.

Research shows that decisions are less effective, when decision makers rush to portfolio solutions or conversely, take too much time to decide on an interpretation (Rudolph, 2003). Effective decision makers will quickly commit to a first frame, and use it to generate a hypothesis, then conduct tests, and gradually construct ever more comprehensive frames. Only a limited set of causal factors are used to develop this first interpretation (Klein et al., 2006b). Thus, a purposeful visual can work as such anchor, as it addresses at least one facet of the portfolio decision problem.

Visuals can also support the next steps in the sensemaking process, as they can trigger questions and instigate re-framing. Ideally, perspectives should embrace typical angles or facets of the portfolio decision problem, such as strategic alignment, risk exposure or project interdependencies. By showing such perspectives visuals will encourage people to consider these perspectives and hence help avoiding typical mistakes in portfolio decisions.

Cognitive fit theory suggests that certain visual designs are more appropriate to show certain perspectives of a problem (Jarvenpaa, 1989; Jarvenpaa & Dickson, 1988; Ware, 2012; Yau, 2011). Hence, if the visuals are purposefully designed, they can display different perspectives of portfolio problem in an effective way. A combination of purposeful visuals will help on the analysis of these multiple perspectives in the portfolio problem.

Therefore, it is reasonable to suggest that decision makers who consciously engage with larger number of purposefully designed visuals are more likely to consider different perspectives of the problem.

Based on typical portfolio management goals and the complexity of most portfolios, Table 1 presents some relevant perspectives for the project portfolio selection. Dashboard A and B (see appendix) show examples of visuals covering some of these perspectives.

Table 1: Perspectives of Portfolio Selection Process

Perspectives	Project portfolio decision goals and complexity	Cognitive task	Examples of potential visuals
Strategic alignment	Ensure alignment between projects and strategic goals	Proportions, relationships, interdependencies,	Scorecard, dashboard, Hoshin Kanri matrix, strategy map, benefit maps,

		patterns, grouping	treemaps, network diagram,
Portfolio balancing (Trade-offs)	Recognition and decision of trade-offs in the pursuit of alternative portfolios	Trade-offs, relationships	Scatter plot, bubble chart, treemaps
Thresholds/ Parameters	Consider threshold and parameters (in terms of constraints or/and expected KPIs)	Differences, focus	Heatmap, Chernoff faces, star chart, tables
Interdependencies	Outcome and benefit interdependencies	Interdependencies, grouping,	Network diagrams, flow charts, benefit maps
	Time and schedule interdependencies	Trends, patterns, interdependencies	Bar chart (Gantt chart), scatterplot
Choice and scenarios	Regard not projects in isolation, i.e. one project against the other, but instead of portfolios against other another – what are the different *portfolio* options?	Memory of tested frames, decision options	Decision tree, fishbone diagram, mind map, scatter plot (efficient frontier graph)
Project variety and specific needs	Regard to qualitative aspects of each project	Holistic understanding of projects beyond pre-established variables	Condensed visuals, e.g. Infographic
Risk (meta-data)	Stochastic nature of future outcomes	Proportions, distributions	Heatmap, histogram, decision tree, pie chart, icon arrays, risk ladders
Lack of available information	Regard not only what is known but where are the knowledge gaps	Patterns, differences, ranges	Scatterplot, star chart, heatmap
Stakeholders	Regard interests of different stakeholders and their potential influence in projects and portfolio	Relationships, proportions	Network charts, treemap

Perspectives should be developed consciously and tailored for each context. Hence, these are not *the* perspectives to be considered in a portfolio selection decision, instead they are deemed 'useful' perspectives that address some of the most common issues and embrace common tasks involved in the project portfolio selection.

Thus, we propose that the use of more purposeful visuals would typically encourage decision makers to embrace more perspectives for a 'good enough' framing of the problem, without being overwhelmed by them. Therefore the use of too few purposeful visuals may indicate a tendency to rash decisions. The use of more purposeful visuals would instigate a more elaborate understanding of the problem and hence increased cognition. Yet too many visuals can overwhelm as well as lead to overconfidence.

Therefore, a mindful use of visuals means choosing *relevant* visuals, i.e. visuals that display relevant perspectives and that are more likely to lead to insights. In a portfolio context this would include those visuals that address typical tasks at hand and help avoid common mistakes in portfolio management.

Proposition 5: Cognition of data is positively influenced by use of purposeful visuals.

3. Methodology

Choice of research methodology

Studying project portfolio decisions is challenging:

(1) Gaining access to boardroom portfolio decisions is difficult, as they are often confidential and closely guarded.
(2) Portfolio decisions are multi-step a process and do not take place at one moment in time, at one level of the organization and in one singular location. Hence, behavior in decision situations is not easily studied.
(3) Research often aims at improving decision quality, which is difficult to measure (Dean & Sharfman, 1996). As portfolio decisions are made under uncertainty and based on incomplete and widely distributed information, there is no definitively "best" decision. Even a post-factum analysis of a decision would not be sufficient to judge decision quality, as it is could not provide information on outcomes of alternative decisions and is often influenced by hindsight bias. Moreover, what constitutes the 'best decision' varies across different stakeholders and interest groups. Hence, it is hard to measure the dependent variable (decision quality).
(4) There are so many variables playing a significant role in portfolio decisions that it is near to impossible to single out the influence of an element in the decision, in this case the visuals and how they have been used.

Taken our research objective and focus on the impact of visuals in individual cognition instead of complex group decisions in organizational settings, we have opted for a human subject experiment.

In an experimental setup, it was possible to control for the three most influential factors in individual decisions, namely, decision features, situational factors and individual differences (Appelt et al, 2011). Situational factors and decision features were constant throughout our carefully design of the experimental scenario, decision task and laboratory conditions. The variables were the visuals (our independent variable), and individual differences. We controlled for individual differences through measurement of subject's decision-making competence (level of confidence and analytical thinking) based on Bruine de Bruin et al (2007) and demographics.

Despite its limitations, experimental research is a useful methodology to approach certain types of questions, in particular to delve into specific aspects of individual and group behavior, which are useful to inform and complement management and organization studies. Examples of experimental research on decision making and even sense making abound, particularly in psychology and behavior economics. Yet, there is scant work on experiments in project management with noteworthy exceptions, e.g. Gersick (1988), Harrison and Harrell (1993), Arlt (2010), Killen (2013). We join their effort to bring experimental research to project management research.

Rational
The objective of the experiment was to test whether the mindful use of visuals can enhance our ability to engage with data from different perspectives. Specifically we proposed that familiarity and use of purposeful visuals would encourage mindfulness.

We therefore developed four portfolio selection dashboards that offered visuals with varying degrees of familiarity/ease and purposefulness (see Figure 2 for an overview of specific visuals in each dashboard, the dashboards are displayed in the appendix).

	Familiar visuals	
	Low	High

Purposeful visuals	Low	C	D
	High	A (yet highly interactive)	B

Figure 2: Rational of sample

Participants were randomly assigned to four cohorts (1, 2, 3 and 4), each using a different dashboard to execute the same decision task. After the decision task, other dependent variables (familiarity, number of visuals used and confidence on decision), demographics and individual differences were assessed through a post-experimental questionnaire, so propositions could be explored. Open research questions were addressed through post-experimental interview and a questionnaire.

The decision task

The development of the experimental scenario, in this case the decision task, is of utmost importance to ensure validity of findings. A balance between realism and simplicity is of critical importance for a behavioral experiment (Grossklags, 2007). The scenario needs to be complex enough to avoid oversimplification and decision with clear 'right' and 'wrong' outcomes. Yet, it should be doable in short duration and by people with limited knowledge on project portfolio management.

We have used the scenario developed and successfully applied in previous research (Arlt, 2010). The scenario was developed based on Arlt's experience with the portfolio of an existing organization. The case was anonymized and modified with the aim to balance simplicity and realism.

The decision plays out in a software development company and is summarized as following: "The portfolio was limited to a manageable choice set of 16 projects. For each project, 15 attributes and metrics were provided, including long-term benefits and cost; short-term benefits, cost and resource needs; project duration; and several additional metrics, relevant to the portfolio decision. These metrics include both short- and long-term ROI, confidence of success, the degree of innovation and the degree of support articulated in committee votes. (Participants were also provided with) a detailed introduction to the experiment, including problem statement, context and strategy, as well as a concise overview for all projects, including project descriptions, explanation of benefits and additional, and decision-relevant information." (Arlt 2010, pp. 183)

The decision task was to choose projects for the next fiscal year, taken the challenges summarized in the bullet points:

- "A (hypothetical) company, BMSI, is a software vendor facing two major challenges: Sharp decline in earnings and significant loss in 2009, and no cash reserves
- Competitive disadvantage due to outdated (software) product
- Consensus-oriented culture, which means projects with only one sponsor have no chance of success
- CEO's strategy consists of three elements: "First and foremost, restore short-term financial success, second, return to developing state-of-the-art solutions and lastly, put the focus back on the customer."
- 16 candidate projects and limited financial and human resources to implement
- The portfolio management team interpreted and further operationalized the strategy: Achieve at least 10% increase in customer satisfaction rating and scrutinize projects without positive ROI" (Arlt, 2010, pp. 184)

Behind the decision task there were three potential strategic options:

- Focus on short-term revenue (choice of projects 13 and 14): this is the best solution as it is the only one that gets close to the target short-term return
- Focus on innovation (choice of a combination of projects 1 to 6): this led to higher innovation but compromised short-term return significantly
- Balanced solution (choice of project 13 plus combination of projects 1 to 6): this provided a quick fix for current software, with a reasonable short-term return, but still prepare for the long-term by starting the innovation program

Next to experimental design principles simplicity and realism is a third important consideration: the provision of performance incentives. Reward payments to the participants were based on customary incentives at University College London; students received GBP 15 for 2 hours and had the opportunity to earn an additional performance reward of GBP 5, if they met or exceeded threshold values for what constituted an “optimal” portfolio selection, including the parameters expected return, innovation and customer satisfaction. The purpose of such rewards is to ensure participants would fully engage with the problem and try to solve it to the best of their abilities, rather than concluding the experiment in the shortest time possible.

Operationalization of variables

Table 3 provides an overview of how variables were operationalized.

Table 3: Overview of operationalization of variables

Type	Construct	Variables	Measurements
Dependent variable	**Cognition**	Decision Quality	Number of mistakes (sum of logical mistakes and constraints exceeded)
			Strategic fit score (combination of resulting figure of three strategic priorities: short-term return, increase in customer satisfaction and innovation) and strategic choice (focus on short-term, on innovation or on a balanced strategy)
	Confidence in decision		Confidence in decision measured in post-experimental survey by Likert scale (from 1, very low, to 5 very high)
Independent variables	**Purposeful**		Most salient feature of Dashboard A and B
			Less salient feature of Dashboard C and D
	Familiarity		Dashboards: Familiarity is expected to be most salient feature of Dashboard B and D, and less salient feature of Dashboard A and C
			Average of familiarity of visuals used. Familiarity was measured in post-experimental survey by Likert scale (from 1, very low, to 5 very high)
	Use	Used visuals	Number of visuals used
		Offered visuals	Number of visuals offered in each Dashboard (A: 1, B: 7, C:6, D:4)
Control variables	**Confidence**	Individual confidence independent from experimental task	Difference between correct answers and confidence in the answers
	Analytical thinking	Ability to understand instructions and think logically	% of correct answers in Bruin and Bruin's test[2]

[2] The questions derives from the measurements on decision competence (Bruine de Bruin, 2007), specifically subject's ability to understand and follow rules. This was of utmost importance in the decision scenario.

Validation of the operationalization of familiarity through visual design

Kruskal-Wallis H test shows that participants were significantly less familiar with Dashboard A compared to other dashboards ($\chi^2(3, 119)=19.001$***). This is not surprising, taken it used a completely different approach for such kinds of decision.

The difference in familiarity between dashboards B, C and D was not significant, but indicative, as shown in the pairwise analysis visualized below.

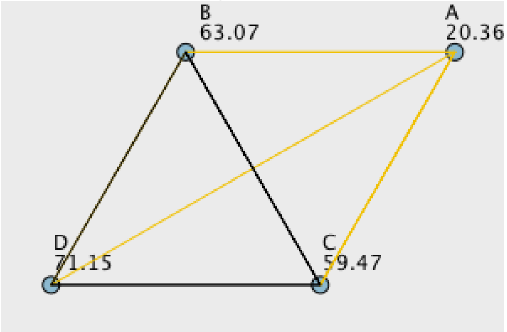

Figure 3: Pairwise analysis of differences on familiarity across dashboards

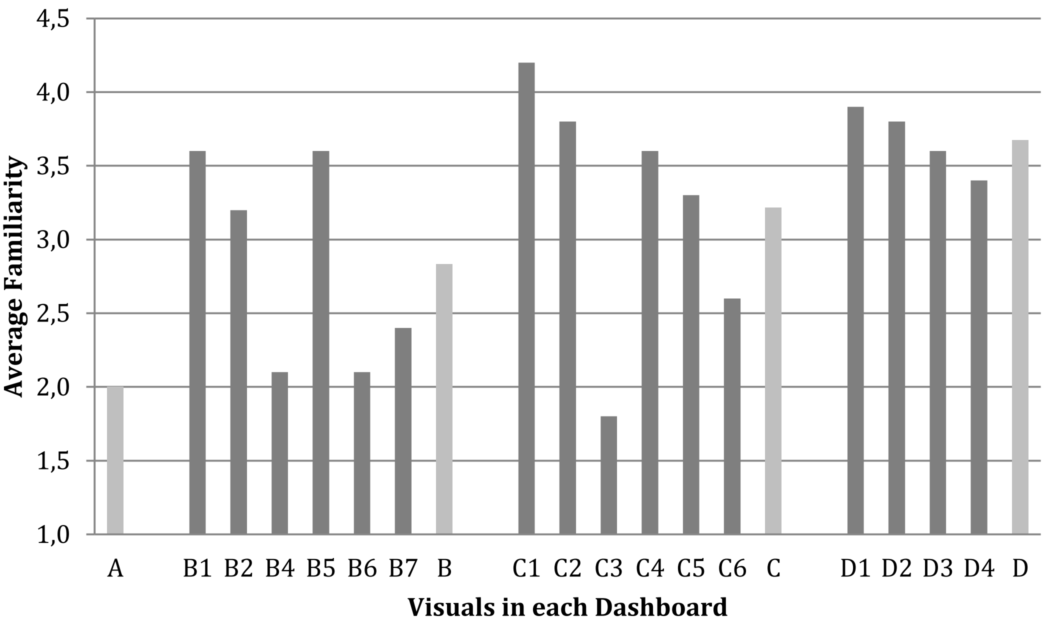

Figure 4: Familiarity of different visuals in dashboard

The graphic below represents the revised operationalization of familiarity through visual design.

Familiarity of visuals

Low
High

Purposeful visuals	Low	C	D
	High	A B	

Figure 5: Revised operationalization of familiarity

Sample
The selection of subjects for the experiment draws on University College London's student population from a variety of disciplines. It is debatable whether student populations can be expected to behave similar to managers, some argue in favor (Ball and Cech, 1996) others, for example in certain group experiments against it (Potters & Van Winden, 2000). Yet students are an appropriate pool of subjects for our experiment for at least three reasons. First, the diversity of disciplines is suitable, as portfolio decisions are likewise multi-disciplinary. As the engagement with visual is influenced by disciplines, it is important to ensure a diversity of disciplines to emulate portfolio decisions. Second, professionals involved in portfolio decisions are often familiar and connected to the projects and data presented to them. They also defend different interests and preferences. Such behavior impacts decisions and is difficult to emulate in experimental settings. This constitutes a challenge to our experiment, as it adds further variables and shadows the impact of visuals on decisions. Experimental setting drawing on student populations helps to reduce such biases, as students are not attached to projects to be selected, nor have they experience in portfolio decisions[3]. Third, although students do not typically have experience in project portfolio decision making, they are expected to deal with the decision tasks appropriately, as they are used to decision problems in the context of problem solving exercises during their studies and it is reasonable to expect a certain level of intelligence required to understand the decision problem.

Participation in the experiment was voluntary and anonymous. Subjects were invited to participate through email sent to all UCL students and reminders through the UCL Psychology Subject Pool. A random sample of 204 participants participated in the experiment. A subset of 39 participants was management students who participated in the experiment as part of their classes on project portfolio management. Post-experimental analysis indicated no significant difference on the decision quality and confidence between these participants and the rest of the sample.

The table below provides an overview of our sample's demographics across different dashboards.

[3] Yet, we are aware that this choice constitutes a challenge for the generalization of the results to portfolio decisions. Future research could explore how design of visuals would act on sensemaking either shifting the attention from a focal point of interest, or emotional attachment to a certain project or strengthening (according to e.g. visual design).

Table 2: Sample's Demographics

		Freq	%	Freq	%	Freq	%	Freq	%	Freq	%
Gender	**Female**	111	54%	29	59%	32	60%	24	47%	26	51%
	Male	90	44%	20	41%	20	38%	26	51%	24	47%
Age	under 25	131	64%	44	90%	29	55%	29	57%	29	57%
	25 - 35	54	26%	2	4%	19	36%	16	31%	17	33%
	36 - 45	12	6%	3	6%	3	6%	4	8%	2	4%
	46 - 60	0	0%								
Education Level	High school	60	29%	33	67%	8	15%	8	16%	11	22%
	Undergraduate degree	72	35%	12	22%	23	43%	22	43%	15	29%
	Post-graduate degree	66	32%	4	8%	19	36%	19	37%	24	47%
	Doctorate	3	1%	0	0%	2	4%	1	2%	0	0%
Specialty	Architecture and Design	10	5%	1	2%	2	4%	5	10%	2	4%
	Biology/ Medicine	30	15%	4	8%	12	23%	7	14%	7	14%
	Business	36	18%	21	43%	8	15%	2	4%	5	10%
	Education	0	0%								
	Mathematics/ Computer Science	28	14%	9	18%	5	9%	9	18%	5	10%
	Natural Sciences	11	5%	2	4%	3	6%	1	2%	5	10%
	Other	34	17%	5	10%	10	19%	8	16%	11	22%
	Social Sciences	51	25%	7	14%	12	23%	18	35%	14	28%
Experience in decisions at work	No	119	58%	36	74%	31	59%	30	59%	22	43%
	Yes	82	40%	13	27%	21	40%	20	39%	28	55%
Missing		3	1%	0	0%	1	2%	1	2%	1	2%

The impact of demographics and control variables on dependent variables was tested through Mann-Whitney-U Test (Gender and Experience in Decisions), Kruskal-Wallis H Test (Area, Age and Education Level) and Pearson's correlation (analytical thinking score, overall confidence score). The analysis suggests that number of mistakes should be controlled for analytical thinking, and short-term score should be controlled for analytical thinking.

4. Data Analysis

Table 3 provides an overview of the data analysis.

Table 3: Overview of findings

Variables	**Decision Quality**	**Confidence**
Number of visuals	*Proposition 1*	*Proposition 2*
• Visuals used	Indicative support	Significant positive correlation (.182*)
Familiarity	*Proposition 3*	*Proposition 4*
• Familiarity with visuals used	Not significant	Significant positive correlation (.232*)
Interactive	*Proposition 5*	
• Dashboard A vs. others	A led to better results (1)	No significant difference between Dashboards
Purposeful	*Proposition 6*	
• Dashboard C<D<B=A	Weak support (1)	No significant difference between Dashboards

(1) Impact of dashboard:

- Number of mistakes: A>C, B>C, by low analytical skills
- Strategic fit score: A more balanced solutions than B, C and D
- Confidence: no statistically significant relationship could be established

Impact of number of visuals in cognition

The objective of the analysis was to determine the impact of the number of visuals used on participant's cognition (basic and strategic understanding) and confidence. The rational behind this analysis is that each visual would encourage participants to take a different perspective and therefore gain a more comprehensive understanding of the problem, yet, the analysis of too many visuals costs time and could lead to information overload, and potentially overconfidence (higher confidence than decision quality).[4]

Participants used a low numbers of visuals, mostly one visual (93 participants), followed by 2 visuals (43 participants), 3 visuals (21 participants) and 4 visuals (only 2 participants, who were considered outliers). This limits our ability to interpret the impact of number of visuals in cognition, and hence to test Propositions 1 and 2.

Within these constraints, data suggests that the impact of number of visuals on basic and strategic understanding of the problem is not as strong as expected. The Kruskal-Wallis H test showed no significant differences on decision scores between people using different numbers of visuals. Number of visuals used did not make a significant difference for participants who scored 75 or higher in the analytical thinking test. For participants with lower analytical skills, using two visuals was significantly better than using three, as suggested in the Kruskal-Wallis analysis[5]. This suggests an indicative support to Proposition 1.

Table 4: Kruskal-Wallis test for impact of no. of visuals across different intelligence scores

Intelligence Score	Dependent Variable	N	X2	Degrees of Freedom	p
25-50	Logical Mistakes	59	2.866	2	.239
	Exceed Constraints	59	8.212	2	.016
	Number of Mistakes	59	7.286	2	.026
>50	Logical Mistakes	92	.686	2	.710
	Exceed Constraints	92	2.430	2	.297
	Number of Mistakes	92	2.774	2	.250

Number of visuals has a weak yet significant positive correlation with confidence of .182*. This suggests that Proposition 2 could not be falsified.

[4] Unlike Dashboard B, C and D, Dashboard A has only one visual structure. Consequently, the sample used for this analysis was only of participants using Dashboards B, C and D, a total of 163 observations. 4 used no visuals and only 2 used four visuals. These cases were considered outliers and disregarded in the analysis. The number of valid observations has hence reduced to 157. Kruskal-Wallis test was used to analyze the differences between samples with more or less visuals.

[5] Yet only six participants used more than three visuals, which limit our results to near to anecdotal. Interestingly though, all six participants with 50 or lower scores who used three visuals, had Dashboard C, the dashboard designed with least purposeful design and familiarity. This indicates that the use of larger number of unfamiliar and not purposeful visuals can lead to detrimental effects in data cognition, particularly amongst more heterogeneous audiences. This indicative relationship was supported by qualitative data in the interviews, where participants reported 'loosing time' in an attempt to analyze unfamiliar visuals, and in particular the Chernoff faces.

Impact of familiar visuals in cognition

The analysis does not indicate considerable impact of familiarity on cognition, as measured by number of mistakes or strategic fit score. A Pearson correlation test point to no significant relationship between familiarity and number of mistakes, and between familiarity and decision scores. A scatter plot confirms that there was no indication of potential non-linear relationship between these variables. The results remained the same also when controlling for analytical thinking scores.

Yet, familiarity had a weak yet significant positive correlation with confidence of .232*.

Thus, the results suggest a similar pattern as that observed in last section. Familiarity had no significant impact on decision quality, failing to support proposition 3, but on confidence, supporting proposition 4. This indicates that familiarity can lead to higher degree of confidence, regardless of the decision quality.

Impact of purposeful visuals in cognition

The results suggest that different dashboards did not have a significant impact on strategic fit scores[6]. We conduct a descriptive analysis and a Kruskal-Wallis H test for the relationship between visual and number of mistakes within each of the different categories of analytical thinking and age, where sample sizes allow. The total number of mistakes and number of logical mistakes is significantly different across dashboards ($\chi2$ (3)=16.230*** and $\chi2$ (3)=18.492***, respectively). Pairwise analysis suggests that A has significantly less mistakes and logical mistakes than C***, and A has less mistakes and logical mistakes than D*, and B less logical mistakes than C*. The expected differences between A and B, B and D and C and D were not statistically significant. This result is further qualified when controlling for analytical thinking.

Analytical thinking scores moderate this relationship. The impact of visual design on number of mistakes was not significant for high analytical thinking scores, $\chi^2(3)=1.776$, but significant for low and average analytical thinking scores, $\chi^2(3) = 15.756$***. A pairwise analysis of results for low and average analytical thinking scores suggest that the number of mistakes is significantly lower in A than C*** and in B than C*. Descriptive analysis suggests results from A and B slightly better than D, which in turn is superior to C. The boxplot 6.2 displays this result graphically[7].

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[6] The analysis of the impact of visuals on the strategic understanding of the problem is done by comparing the differences between strategic fit score (short-term return, customer satisfaction and innovation and the balance between these scores) for participants using dashboards A, B, C and D. The analysis indicated that only increase in customer satisfaction score was significantly different across dashboards, $\chi^2(3)=10.827$*, where A led to significantly higher customer satisfaction scores than C*. Yet, no significant relationship has been identified when controlling for analytical thinking.

[7] The impact of visuals on the number of mistakes remained similar when accounting for differences in age groups. The effect of analytical thinking scores on the relationship between visual design and number of mistakes remains across age groups.

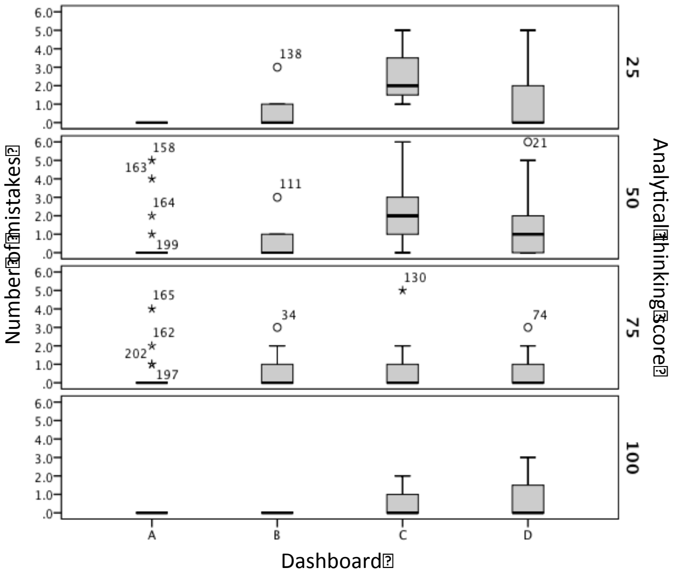

Figure 6: Boxplot of number of mistakes across dashboards and analytical thinking scores

There is no significant impact of choice of specific visuals on strategic fit score or confidence,[8] but on number of mistakes, namely the use of Gantt chart led to a significant decrease on logic mistakes (U (51)=240.000*). This is not surprising, taken such relationship has been already empirically established in previous research (MacNeice, 1951). Yet it supports the argument that examining different and relevant perspectives matter in portfolio decisions. Due to small sample sizes, the impact of use of other visuals could not be statistically tested.

Thus, overall across the tests, Dashboard A and B yield better results than D, and D better than C. This suggests that purposefulness encourages improved cognition, regardless of potential low familiarity of the visuals used. Yet, the influence of visuals was only significant for basic understanding of the problem and for participants who had an average or low analytical thinking score. Therefore Proposition 5 was only partly supported.

As with regards to confidence, Kruskal-Wallis H Test suggests that use of purposeful visuals had no significant impact on confidence ($\chi^2(3)=5.264$, p=.153).

5. Conclusion

We now turn back to the motivation of this study: project portfolios are increasingly complex and information used to support decisions is vast, uncertain, ever changing and ambiguous. Visuals are often used to support portfolio decisions, yet extant research suggests that they could help cognition of data, but they can also hinder it. How can visuals improve our ability to make sense of the data mindfully, i.e. to analyze more data leading to improved decisions, while not becoming overwhelmed nor overconfident?

Our study suggests that visuals are a double-edged sword. As participants used limited number of visuals, we could not test fully explore the non-linear relationship between number of visuals and decision quality postulated in Proposition 1. Overall, the results indicate that the number of visuals had no

[8] U(51)=276.000, p=.307.

significant impact on decision quality, but on confidence, and let to overconfidence. Hence the study supports Proposition 2. This suggests that as with the use of more data (Omodei et al., 2005), the use of more visuals intensifies confirmation bias. The study also provides weak indication that the use of larger number of visuals can overwhelm, as with the use of more data (Tsai et al, 2008).

As with the use of larger number of visuals, the finding suggests that familiarity increases the comfort level and acceptance, even leading to higher confidence levels, supporting proposition 4. Yet, the study also suggests that offering non-purposeful and not familiar visuals lead to inferior decisions than offering non-purposeful but familiar visuals. One explanation is that if the visual is familiar, decision makers can understand whether the visual provides interesting insights more quickly and accurately, and hence dismiss irrelevant visuals and become less overwhelmed. Thus, familiarity with visuals contributes to an increased mindful engagement with visuals, yet marginally. Thus, we found limited support to Proposition 3.

The use of specific visuals can have a positive impact on decision quality; the results suggest that the use of Gantt chart reduced the number of mistakes significantly. The results therefore provide some support to the argument that the use of more visuals is not necessarily advantageous, yet examining relevant perspectives matter in portfolio decisions. Hence the findings provide some support to Proposition 5.

Yet, the experimental results suggest that there is a significant impact of purposeful visuals on decision quality but not on confidence. The same pattern was observed when changing from static to interactive dashboards: while the decision quality improved significantly, confidence was not affected. The above pattern is still significant after controlling for participants' overall decision confidence[9]. What is counter-intuitive about this result is that some participants, who used better-designed visuals, made better decisions but were not more confident about their decisions, and other participants, who used worse-designed visuals, made worse decisions, but were confident.

A potential explanation for the findings is that some participants made the right decisions by chance, and not because they understood the problem. This may explain the results of some participants using Dashboard A. Dashboard A is interactive and reduces structural complexity of the problem dramatically. The visual does not allow portfolio decisions that disrespect interdependencies between projects, resource and budget constraints. Moreover, numbers can be retrieved, but they are not salient feature of the visual. Hence, participants can make correct decisions regardless of their understanding. Indeed, qualitative data suggests that only few participants appreciated the reduced complexity and used the interactive feature of Dashboard A, seeking a portfolio mix by trial and

[9] Overall confidence is the confidence level that participants have in their decisions – independent from the experiment, i.e. whether they tend to be over- or under-confident.

error, but also in a thoughtful manner to facilitate and improve decisions and focus on a more strategic understanding of problem.

Several participants were satisfied with just finding a feasible portfolio choice, and not making mistakes that would violate portfolio constraints; they didn't appear to have used the tool to understand the problem. Instead, participants 'played' with the visual, and made decisions by trial and error. It is reasonable to suggest that these participants would have better results, but not necessarily higher confidence, as they did not truly understand what they were doing.

However, based on qualitative data collected in post-experimental interview and open-ended questions in questionnaire suggest that this explanation does not provide a full account of the findings. A potential alternative and complementary explanation is that participants had low awareness of how visuals help (or hinder) decisions. This means that for example participants may have used the visuals correctly, but did not trust what they were seeing. For example, they understood the relationships through Gantt chart and hence avoided logical mistakes, but were not absolutely sure that the Gantt chart displayed all interdependencies. Likewise, some participants preferred static dashboards with detailed information about projects, as they missed the detailed information to make better strategic choices and justify them. This lack of trust may have negatively influenced confidence.

Mistrust in visuals can be positive and indicate high levels of visual literacy. Visuals are persuasion mechanisms, never neutral and hence should be received with a health degree of mistrust, and deserve critical scrutiny, for example, the following questions should be asked: What data has been filtered out? Which perspectives does it show and which ones does it not show? What does the author of visuals want to say? What are his/her interests? Yet, bare mistrust without critical engagement would rather suggest an irrational suspicion of visuals. In this case, improvements in visual literacy would be beneficial. In this specific experimental setting, mistrust in purposeful visuals such as the Gantt chart suggests rather the need to improve visual literacy.

This finding has implications to practice. Portfolio decisions are to a large extent an iterative and reflective process. While this is difficult to emulate in a 45 minute experiment, in reality, interacting with data, observing the consequences of choices, reflecting on choices and trade-offs and thereby increasing confidence over time is important for the decision process. Thus, unlike in an experiment, when new visuals are introduced, it is important to make decision makers comfortable with the use of new visuals, so they can achieve the intended objectives, i.e. a mindful engagement with visuals, where data can be analyzed from different perspectives to make informed and balanced project portfolio decisions.

Limitations and future research

The key limitation of the research design was the unexpected heterogeneity of the participant population in regards to their ability to solving the problem, which is partly useful, as it represents heterogeneity in practice, yet let to methodological difficulties and sample size problems for some analysis. In addition, design judgments are subjective and introduce potential distortions, as for example a visual may be more or less purposeful than intended, even if design criteria were adhered to. Moreover, as participants also engaged with a limited number of visuals, the nonlinear relationship between number of visuals used and cognition of data, proposition 2a, could not be empirically validated. Lastly, generalizing the findings of the experiment for decisions beyond the PPM context is problematic, given the specific scope of the experiment. These limitations are one aspect that leads to the need for further research, which will be discussed in the next section.

Based on the results and limitations of this research, we suggest to further:

- Explore the same research questions and propositions of our research effort, but in different experimental setups.
- Develop a contingent understanding of the impact of visuals across different types of projects and portfolios.
- Explore the relationship between number of visuals, confidence and cognition in more depth, e.g. would it be moderated by good visual design?
- Study the relationship between familiarity, confidence and cognition, particularly over longer periods of time
- Focus on the actual design and use of visuals in portfolio decisions both in individual and groups in organizations.

Regarding the PPM area, we contend that current research in portfolio management is still dominated by normative guidance from the 1990s. We therefore join Martinsuo (2013) and Petit and Hobbs (2010) in a call to broaden our understanding of project portfolios, and reconnect research with the actual portfolio practices. In particular, we suggest research that explores decisions in projects and portfolio contexts. Specifically, there is a need to expand the work in the area and improve and strengthen its connection with decision theory. Taken the context of projects as temporary organizations and portfolios as a bridge between temporary and permanent organizations, the behaviors and dynamics of decision making and sensemaking are likely to be different, and hence there is a potential to contribute not only to project management literature but also to general management and decision theory.

Our research effort took an innovative approach in terms of its methodology. Experimental research is still under-explored in project management research. Yet it is a powerful way to address certain types of research questions, such as individual and group behaviors in temporary organizations. Therefore we endorse this methodology for such research in the future. We also encourage a stronger acknowledgement of visuals as a valid and important source of data in research. Visuals are integral part of project and portfolio management practices, yet our studies often fail to embrace visuals as a source of data.

Finally, we call for further studies on data exploration in the project management contexts. For example, how can the management of projects and portfolios both harness and exploit the massively increasing magnitude of available data for purposes of analytics and decision making? How can respective tools, including visuals, be effectively used to cope with increasing complexity of projects and programs?

Our research effort aims at contributing to an increased awareness of the importance of visuals and encouraging their mindful design and use in the project portfolio practice as well as in research.

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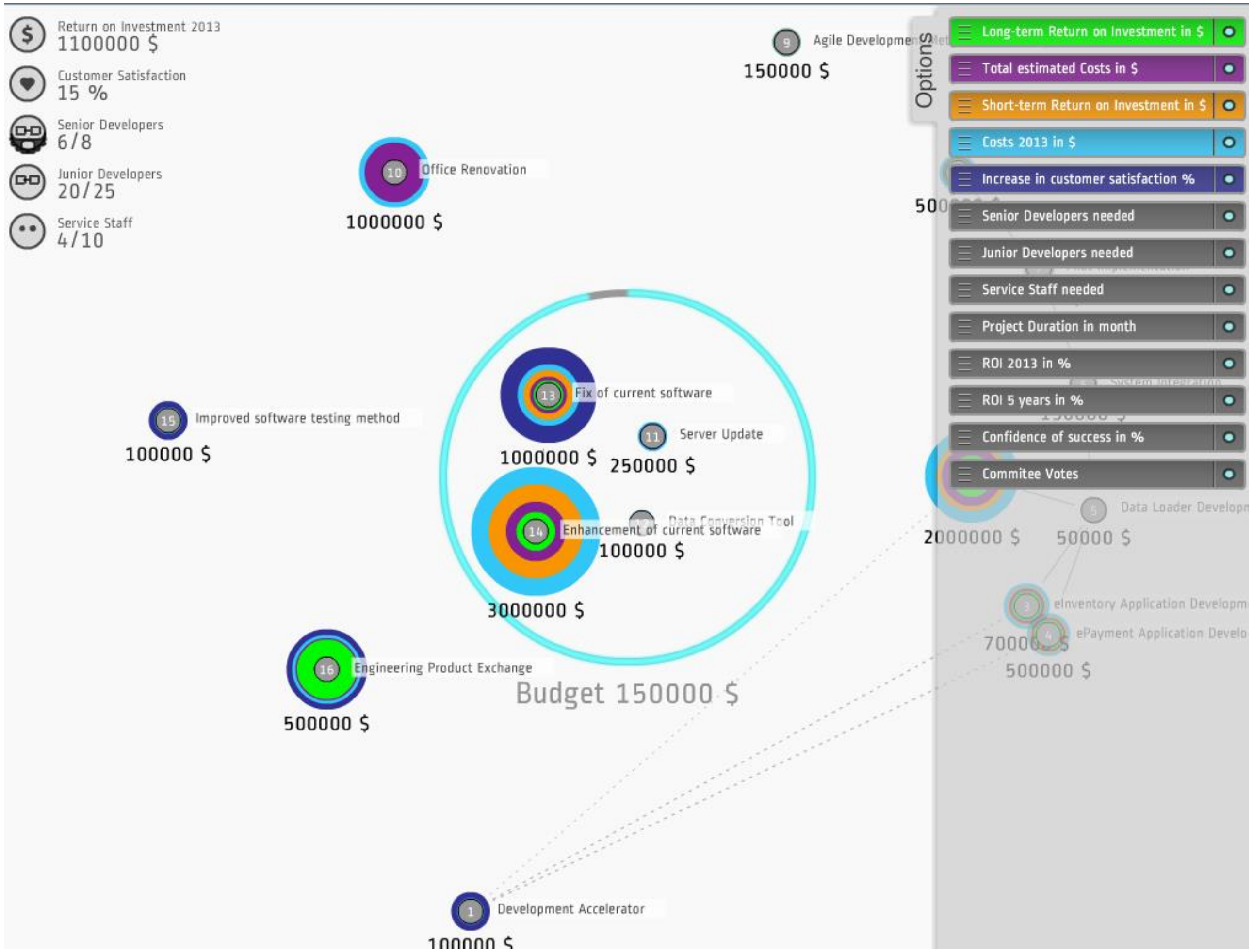
Appendix

Table A1: Retrospective evaluation of visuals in each dashboard

Dashboard	**Visual**	**Visual description**	**Mindfulness encouraged by**	
			Purposefulness	Familiarity
A			+	0 (yet very intuitive)
B	**Overall retrospective evaluation**		+	0
	B1	Table augmented with visuals	+	+
	B2	Gantt chart	+	0
	B3	Short description of projects	+	+
	B4	Flow chart displaying thematic, financial and temporal interdependencies between projects	+	-
	B5	Reminder of strategic priorities	+	+
	B6	Treemap (proportional contribution of each project to each of the key decision variables)	+	-
	B7	Bubble chart	0	-
C	**Overall retrospective evaluation**		-	0
	C1	Table	+	+
	C2	Short description of projects	+	+
	C3	Chernoff face (it uses facial characteristics to represent decision variables)	-	--

	C4	Pie chart	-	+
	C5	Traffic light in table format	-	+
	C6	Circle proximity represents Interdependencies between projects	-	-
D	**Overall retrospective evaluation**		**-**	+
	D1	Table	+	+
	D2	3D Bar chart displaying use of resources	-	+
	D3	3D Bar chart displaying random decision variables	-	+
	D4	3D Pie chart	-	+

Dashboard A

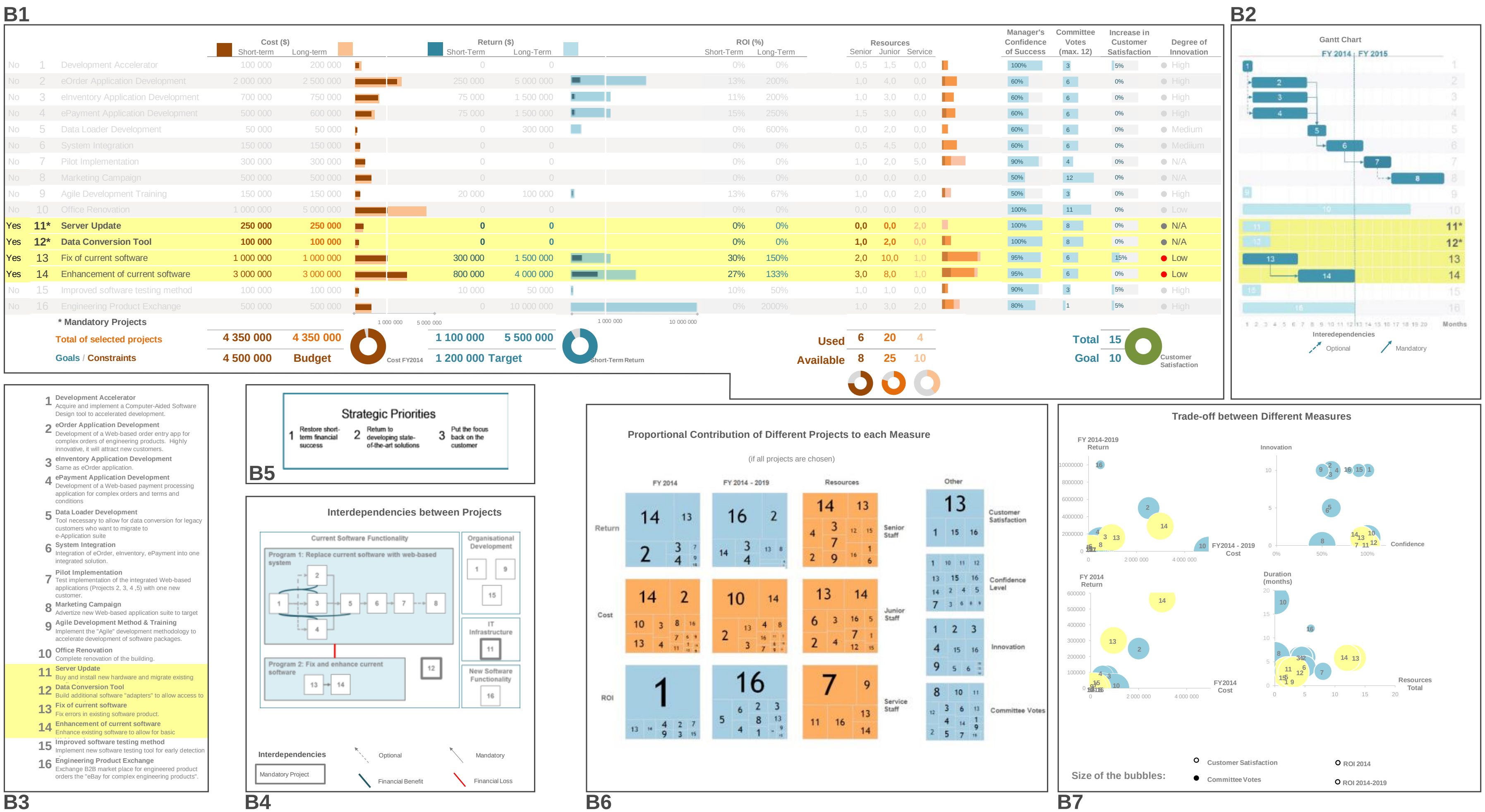


Interactive dashboard functions as following:

- Projects are represented by different nodes; the lines connecting them represent their interdependency.
- Selection of projects is done by dragging and dropping the 'projects' to the central circle.
- Benefits and resource constraints of the current selection are displayed on the left menu
- Decision parameters are displayed by the rings around each node.
- User can choose which parameters to be displayed on the right menu.

This dashboard has been developed by 'Solve Different' research project, which was supported by the Peter Pribilla Foundation. We thank for the permission and encouragement to re-use it in this research.

Dashboard B


B1
B2
B3
B4
B5
B6
B7
* Mandatory Projects
Total of selected projects
Goals / Constraints
Budget
Target
Used
Available
Total
Goal
Gantt Chart
Strategic Priorities
1 Restore short-term financial success
2 Return to developing state-of-the-art solutions
3 Put the focus back on the customer
Interdependencies between Projects
Proportional Contribution of Different Projects to each Measure
(if all projects are chosen)
Trade-off between Different Measures
Size of the bubbles:
1 Development Accelerator
2 eOrder Application Development
3 eInventory Application Development
4 ePayment Application Development
5 Data Loader Development
6 System Integration
7 Pilot Implementation
8 Marketing Campaign
9 Agile Development Method & Training
10 Office Renovation
11 Server Update
12 Data Conversion Tool
13 Fix of current software
14 Enhancement of current software
15 Improved software testing method
16 Engineering Product Exchange

Dashboard C

C1

[Project Portfolio]

SELECT PROJECTS			Cost ($) FY2014	Cost ($) 2014-2019	Return ($) FY2014	Return ($) 2014-2019	ROI (%) FY2014	ROI (%) 2014-2019	Resources Senior Staff	Resources Junior Satff	Resources Service Staff	Duration
No	1	Development Accelerator	100 000	200 000	0	0	0%	0%	0,5	1,5	0,0	1
No	2	eOrder Application Development	2 000 000	2 500 000	250 000	5 000 000	13%	200%	1,0	4,0	0,0	6
No	3	eInventory Application Development	700 000	750 000	75 000	1 500 000	11%	200%	1,0	3,0	0,0	6
No	4	ePayment Application Development	500 000	600 000	75 000	1 500 000	15%	250%	1,5	3,0	0,0	6
No	5	Data Loader Development	50 000	50 000	0	300 000	0%	600%	0,0	2,0	0,0	2
No	6	System Integration	150 000	150 000	0	400 000	0%	267%	0,5	4,5	0,0	4
No	7	Pilot Implementation	300 000	300 000	30 000	30 000	10%	10%	1,0	2,0	5,0	3
No	8	Marketing Campaign	500 000	500 000	0	1 000 000	0%	200%	0,0	0,0	0,0	6
No	9	Agile Development Training	150 000	150 000	20 000	100 000	13%	67%	1,0	0,0	2,0	1
No	10	Office Renovation	1 000 000	5 000 000	0	0	0%	0%	0,0	0,0	0,0	18
Yes	**11***	**Server Update**	**250 000**	**250 000**	**0**	**0**	**0%**	**0%**	**0,0**	**0,0**	**2,0**	3
Yes	**12***	**Data Conversion Tool**	**100 000**	**100 000**	**0**	**0**	**0%**	**0%**	**1,0**	**2,0**	**0,0**	3
Yes	13	Fix of current software	1 000 000	1 000 000	300 000	1 500 000	30%	150%	2,0	10,0	1,0	6
Yes	14	Enhancement of current software	3 000 000	3 000 000	800 000	4 000 000	27%	133%	3,0	8,0	1,0	6
No	15	Improved software testing method	100 000	100 000	10 000	50 000	10%	50%	1,0	1,0	0,0	2
No	16	Engineering Product Exchange	500 000	500 000	0	10 000 000	0%	2000%	1,0	3,0	2,0	12

* Mandatory Projects

	Cost FY 2014	Cost FY2014-19	Return FY 2014	Return FY2014-19		Senior Staff	Junior Staff	Service Staff
Total of Selected Projects	**4 350 000**	**4 350 000**	**1 100 000**	**5 500 000**	Used	**6**	**20**	**4**
Goals / Constraints	**4 500 000**		**1 200 000**		Total	**8**	**25**	**10**

C2

1 **Development Accelerator**
Acquire and implement a Computer-Aided Software Design tool to accelerated development.

2 **eOrder Application Development**
Development of a Web-based order entry application for complex orders of engineering products.

3 **eInventory Application Development**
Development of a Web-based order entry application for complex orders of engineering products.

4 **ePayment Application Development**
Development of a Web-based payment processing application for complex orders and terms and conditions.

5 **Data Loader Development**
Tool necessary to allow for data conversion for legacy customers who want to migrate to e-Application suite.

6 **System Integration**
Integration of eOrder, eInventory, ePayment into one integrated solution.

7 **Pilot Implementation**
Test implementation of the integrated Web-based applications (Projects 2, 3, 4 ,5) with one new customer.

8 **Marketing Campaign**
Advertize new Web-based application suite to target customers.

9 **Agile Development Method & Training**
Implement the "Agile" development methodology to accelerate development of software packages

10 **Office Renovation**
Complete renovation of the building

11 **Server Update**
Buy and install new hardware and migrate existing applications.

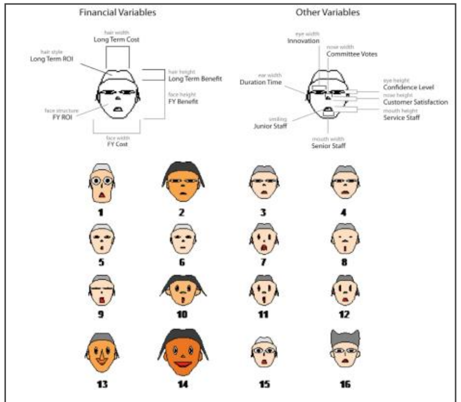
12 **Data Conversion Tool**
Build additional software "adapters" to allow access to customer data.

13 **Fix of current software**
Fix errors in existing software product.

14 **Enhancement of current software**
Enhance existing software to allow for basic Webbased access.

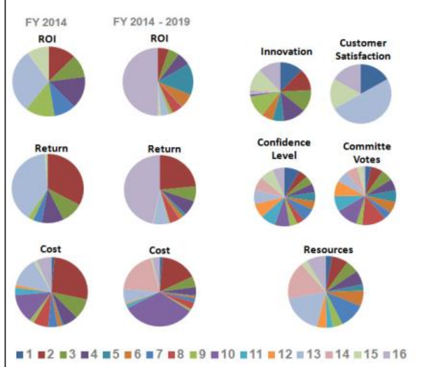
15 **Improved softwaretesting method**
Implement new software testing tool for early detection of software errors.

16 **Engineering Product Exchange**
B2B market place for engineered product orders - the "eBay for complex engineering products".



Chernoff Faces:
spot extremes and specific features. 1

C3



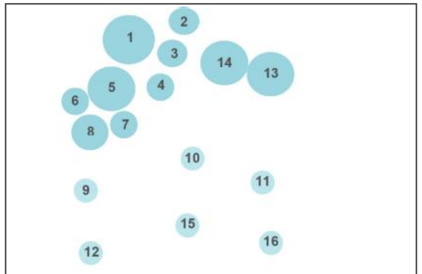
Pie Charts:
overview of each cathegory

C4

	Manager's Confidence Level of Success	Committee Votes (max. 12)	Innovation	Increase in Customer Satisfaction
1	100%	3	High	5%
2	60%	6	High	0%
3	60%	6	High	0%
4	60%	6	High	0%
5	60%	6	Medium	0%
6	60%	6	Medium	0%
7	90%	4	N/A	0%
8	50%	12	N/A	0%
9	50%	3	High	0%
10	100%	11	Low	0%
11*	100%	8	N/A	0%
12*	100%	8	N/A	0%
13	95%	6	Low	15%
14	95%	6	Low	0%
15	90%	3	High	5%
16	80%	1	High	5%

Traffic Lights

C5



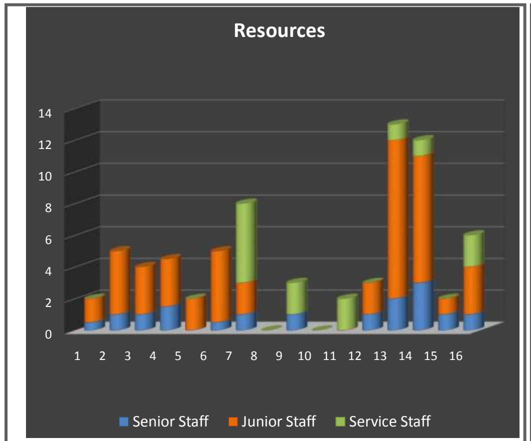
Interdependencies Graph:
distance bewteen the bubles is relative to the interdependecies between the projects.

C6

Dashboard D

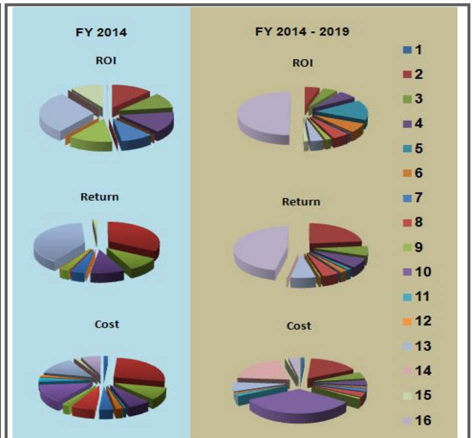
D1

		Project	Cost ($) FY2014	Cost ($) 2014-2019	Return ($) FY2014	Return ($) 2014-2019	ROI (%) FY2014	ROI (%) 2014-2019	Resources Senior	Resources Junior	Resources Serivce	Duration	Confidence Level	Votes (max. 12)	Innovation	Customer Satisfaction
No	1	Development Accelerator	100 000	200 000	0	0	0%	0%	0,5	1,5	0,0	1	100%	3	10	5%
No	2	eOrder Application Development	2 000 000	2 500 000	250 000	5 000 000	13%	200%	1,0	4,0	0,0	6	60%	6	10	0%
No	3	eInventory Application Development	700 000	750 000	75 000	1 500 000	11%	200%	1,0	3,0	0,0	6	60%	6	10	0%
No	4	ePayment Application Development	500 000	600 000	75 000	1 500 000	15%	250%	1,5	3,0	0,0	6	60%	6	10	0%
No	5	Data Loader Development	50 000	50 000	0	300 000	0%	600%	0,0	2,0	0,0	2	60%	6	5	0%
No	6	System Integration	150 000	150 000	0	400 000	0%	267%	0,5	4,5	0,0	4	60%	6	5	0%
No	7	Pilot Implementation	300 000	300 000	30 000	30 000	10%	10%	1,0	2,0	5,0	3	90%	4	0	0%
No	8	Marketing Campaign	500 000	500 000	0	1 000 000	0%	200%	0,0	0,0	0,0	6	50%	12	0	0%
No	9	Agile Development Training	150 000	150 000	20 000	100 000	13%	67%	1,0	0,0	2,0	1	50%	3	10	0%
No	10	Office Renovation	1 000 000	5 000 000	0	0	0%	0%	0,0	0,0	0,0	18	100%	11	1	0%
Yes	**11***	**Server Update**	**250 000**	**250 000**	**0**	**0**	0%	0%	**0,0**	**0,0**	**2,0**	**3**	100%	8	0	0%
Yes	**12***	**Data Conversion Tool**	**100 000**	**100 000**	**0**	**0**	0%	0%	**1,0**	**2,0**	**0,0**	**3**	100%	8	0	0%
Yes	13	Fix of current software	1 000 000	1 000 000	300 000	1 500 000	30%	150%	2,0	10,0	1,0	6	95%	6	1	15%
Yes	14	Enhancement of current software	3 000 000	3 000 000	800 000	4 000 000	27%	133%	3,0	8,0	1,0	6	95%	6	1	0%
No	15	Improved software testing method	100 000	100 000	10 000	50 000	10%	50%	1,0	1,0	0,0	2	90%	3	10	5%
No	16	Engineering Product Exchange	500 000	500 000	0	10 000 000	0%	2000%	1,0	3,0	2,0	12	80%	1	10	5%
		Mandatory Projects	Cost FY 2014	Cost FY2014-19	Return FY 2014	Return FY2014-19										
		Total of Selected	4 350 000	4 350 000	Total of Selected 1 100 000	5 500 000		Used	6	20	4		98%	Mean values 7,00	0,50	0,04
		Constraint	4 500 000		Goal 1 200 000			Total	8	25	10					



D2

D3



D4